Spotnik **Designing Distributed Machine Learning for Transient Cloud** Resources

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Distributed ML

Train a machine learning model





Distributed ML

Train a machine learning model





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Challenges of distributed ML

- Distributed ML is resourcehungry
- Accelerated resources are expensive

³Shoeybi, Mohammad, et al. Megatron-LM: Training multi-billion parameter language models using gpu model parallelism, 2017



Example Megatron-LM³

- Training of BERT-like model
- 512 V100 GPUs
- One epoch (68,507 iterations) takes 2.1 days
 - Cost on Azure: \$92,613

Transient cloud resources

- Examples: AWS Spot instances, Azure Spot VMs
- Follows the law of a free market
- Revocations
 - Notifications



- Economic incentive
 - Offers a cost reduction of up to 90%¹

A Megatron-LM epoch would drop from \$92,613 to \$15,152

¹https://azure.microsoft.com/en-us/pricing/spot/





Imperial College London Implications of transient resources

- New workers become available or old workers get revoked System must cope with disappearing resources
- Changes can happen at any time
 - System must ensure consistency of updates





Size

Implications of transient resources

- New workers become available or old workers get revoked System must cope with disappearing resources
- Changes can happen at any time -> System must ensure consistency of updates

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• Cluster sizes are unknown beforehand System must adapt to different conditions





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- Tensorflow and Pytorch
- Changes to the cluster are not considered
- Recovery takes about 20 seconds with ResNet50 and ImageNet







Current approaches: Hybrid

- Mix dedicated resources with transient resources
- training state is save



²Harlap et al. Proteus: agile ML elasticity through tiered reliability in dynamic re- source markets. EuroSys, 2017



• Proteus²: Placement of parameter server on dedicated resources so that the



Challenges	
Workers become available or get revoked	
Changes can happen at any time	Ensur
Cluster sizes are unknown beforehand	Chan



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Solutions

Reuse communication channels for synchronisation to repair the cluster

re **atomic model updates** by waiting for all synchronisations to finish first

ge the synchronisation strategy based on the number of workers



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Revocation recovery algorithm

- Handle revocations within a ring topology
- Number of total messages is bounded by $O(N \cdot K)$ messages
 - K is the number of simultaneous revocations
 - N is the number of workers

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→ Scale to many transient resources

No reliance on revocation notifications



Revocation recovery algorithm

Repairing a broken all-reduce ring



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Worker	Membership
Ο	[0, 1, 2, 3, 4, 5]
1	[0, 1, 2, 3, 4, 5]
2	[0, 1, 2, 3, 4, 5]
3	[0, 1, 2, 3, 4, 5]
4	[0, 1, 2, 3, 4, 5]
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Revocation recovery algorithm





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Revocation recovery algorithm





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Revocation recovery algorithm





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Atomic worker state update

Pipelined synchronisation





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Atomic worker state update

- Pipelined synchronisation
- Revocations can happen meanwhile → Partial update leads to inconsistency







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Atomic worker state update

- Atomicity: Wait for all synchronisation communications to finish
- Discard updates if communication fails







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Imperial College London **Adaptive synchronisation strategies**

- Support a range of synchronisation primitives
 - collective and point-to-point synchronisation
- Monitor a metric
 - Number of workers



Imperial College London **Adaptive synchronisation strategies**

- Support a range of synchronisation primitives
 - collective and point-to-point synchronisation
- Monitor a metric
 - Number of workers
- Define a policy in the beginning
 - When to choose which sync strategy





Evaluation

How does the recovery latency change with increasing number of revocations?



No significant increase of recovery latency if the number of revocation increases



Evaluation

How much does the training slow down if we use atomic worker state updates?



- 32 workers Hardware
- Azure NC6 VMs
 - Nvidia K80
- Software
- KungFu 0.2.1
- **Tensorflow 1.15**





Throughput decrease is small

Evaluation

How does the throughput change, if the cluster changes?





Evaluation

How does the throughput change, if the cluster changes?





Evaluation

How does the throughput change, if the cluster changes?





Changing clusters need adaptation



Conclusion

- Transient cloud resources offer potential to save money for ML training



No system that runs exclusively on transient resources and has low overhead

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- No system that runs exclusively on transient resources and has low overhead
- Repair cluster with low overhead
 Ensure consistent model updates
 - Adapt to changes of the cluster



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KungFu github.com/lsds/KungFu



Adapt to changes of the cluster

Conclusion

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- No system that runs exclusively on transient resources and has low overhead
- Repair cluster with low overhead Spotnik • Ensure consistent model updates Adapt to changes of the cluster
 - KungFu github.com/lsds/KungFu

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